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Geomatics and bioenergy feasibility assessments: Taking stock and looking forward

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ABSTRACT

Renewable energy resources are spatially distributed, and their potential to contribute to societal energy supplies is dependent on local geographic nuances. To provide relevant and robust baseline information, these spatial qualities must be considered when assessing resource availability or technology performance. This is the impetus behind the application of geomatics in the field of renewable energy. Given that each renewable energy source option has unique geographic qualities, a one-size-fits-all analytical approach is not possible. It is thus important to examine how the geographic qualities of specific renewable energy options are managed in the methodological approaches that are used to assess them. To this end, this paper reviews the ways in which geomatics has been used to provide geographic information about bioenergy feasibility, and to solve fundamental bioenergy measurement problems in terms of distinguishing actual from potential feedstock, quantifying multiple biomass supply options, and assessing the scope of conversion platforms. Particular attention is given to data quality, the commensurability of data models and the energy sources they attempt to visualize and analyze, the methods used for facility location decisions, and the capacity to perform site-specific analyses of technology performance. The paper also discusses the ways that the 'static' nature of geographic information can be overcome to take seriously the temporal issues that are related to bioenergy feasibility. Moving forward, bioenergy assessments must begin with a comprehensive resource assessment and consider a range of conversion options. This baseline information will enable bioenergy to be taken seriously in energy investment decisions.

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1. Introduction

The most important questions surrounding renewable energy are related to supply and technical capacity. The answers to these questions are site-selective. In other words, site-specific logistical issues and energy fluxes determine the extent to which renewable energy sources can be liberated at a scale relevant for societal consumption [1]. To provide relevant and accurate information to decision-makers geographic information is required. Conducting ground-based research of all potential locations for renewable energy technologies is, however, a logistical impossibility. Fortunately, digital spatial technologies including remote sensing and geographic information systems, which are collectively referred to as geomatics, automate and assist spatial analysis and visualization with (ever-increasing) detail over broad spatial extents. As such, the application of geomatics is quickly becoming a standard for renewable energy analysis.

Sorensen and Meibom [2] and Dominguez and Amador [3] provide reviews of how geomatics has been applied in the field of renewable energy. It is important to note, however, that each renewable energy source option – i.e., solar, biomass, hydro, wind, geothermal – has unique geographic qualities [3]. As such, reviews and comprehensive dialogue of how geomatics has been employed to assess the spatial qualities of *specific* renewable energy sources are necessary but currently lacking. To this end, this paper reviews the ways in which geomatics has been used to solve fundamental bioenergy measurement problems in terms of distinguishing actual from potential feedstock, quantifying multiple biomass supply options, and assessing the overwhelming scope of bioenergy conversion platforms and technological configurations from which useable forms of energy are made available.

This review is structured around the hierarchical nature of bioenergy availability as identified in [4]. Three exhaustive categories have been chosen to represent this hierarchy: theoretical energy resources, exploitable energy resources, and net energy yields. The next three sections review how investigators achieve these respective levels of detail using geomatics. In the fourth section, before concluding, the extent to which these approaches engage specific bioenergy measurement problems is assessed in such a way as to guide future analyses. Particular attention is given to data quality, the commensurability of data models and energy sources, the use of derived and ancillary data, location theory and analyses, and the capacity to perform site-specific performance analyses.

2. Bioenergy resource assessments at the theoretical level of analysis

Theoretical energy availability is the total energy content per unit area from a given energy source option at any moment in time. This is also referred to as the 'physical limit' [5], because in theory it is a measurement that considers only the laws of physics relevant to the energy source. There are three principal sources of biomass that constitute theoretical bioenergy availability: forest fuels, agricultural fuels, and bio-wastes. This categorical variability begins to flesh out the analytically taxing nature of comprehensive theoretical bioenergy assessments, and indeed few attempts have been made to capture all three categories: but see [6–8].

Geographic information to derive theoretical bioenergy values can be stored, represented, and analyzed digitally in vector or raster data formats. The former represents spatial data as points, lines, and polygons and is closely related to 'classic' cartographic techniques. It is adept at spatially referencing detailed thematic information – e.g., volume, moisture contents, and stem density – that is collected on the ground. The latter is a grid-based model which represents spatial data as a set of unique values in tabular format. This data is collected via remote sensing. Each cell has a single value that is the result of the interaction of electromagnetic radiation between ground cover and the remote sensor. A contiguous image is generated from these values, and thus raster data models are adept at representing spatial continuity. Both of these data models have been used when collecting, visualizing, and analyzing geographic information regarding theoretical energy availability from the biomass sources listed above.

2.1. Forest fuels

Vector data models are used to spatially reference ground-based forest data such as national forest inventories (NFI), independent field research, or mail survey information from land owners. This information usually results in a large quantity of data, and so it is common to aggregate this data by way of neighbourhood operators. Ranta [9] aggregates NFI stand-level data into 100 km^2 polygons using Delaunay triangulation. Viana et al. [10] use a similar method but are severely limited by geographic data and are thus forced to aggregate their values over the entire study site. Nord-Larson and Talbot [11] aggregate their data using municipal boundaries. In each case the boundaries to which the data has been aggregated has attached to it an energy density that is calculated using the structural characteristics of the stands within the polygon. The center, i.e., the anchor point, of a given polygon represents the point of supply for subsequent costing analyses, which helps to simplify transportation costing techniques. Lopez-Rodriguez et al. [12] use the species-oriented land classification technique adopted by Spain's NFI data collection procedures. The authors map out 'stratums' which are polygons characterized by statistical homogeneity of species predominance, species development, species occupation, and percentage of land cover. Each stratum is associated with a specific 'biomass fraction', from which forest residues are calculated.

Remotely sensed data can be employed as an alternative to, or in combination with, the data discussed above. Using remotely sensed data to estimate biomass has been prevalent since the early 1990s. Recent reviews are provided in [13,14]. Only recently, however, have remote sensing techniques been applied to *bioenergy* assessments [15]. For reasons of availability and cost, most studies to date have used multispectral satellite imagery. Bioenergy investigators quantize ratios and indices from the photosynthetically active regions of the electromagnetic spectrum to identify and characterize forest fuels. The most common approach is to correlate a Normalized Differential Vegetation Index (NDVI) transform with ground-based measurements of biophysical properties. This transform is a simple spectroscopic model that uses the normalized difference between reflectance values in the near infra-red (NIR) and the red (RED) bands to measure 'greenness' (see Eq. (1)).

$$\mathrm{NDVI} = \frac{\mathrm{NIR} - \mathrm{RED}}{\mathrm{NIR} + \mathrm{RED}} \tag{1}$$

Pixel values closest to one are locations with highly active vegetation, and pixel values close to negative one are non-vegetated surfaces. In some cases, depending the origin and detail of ground verification (which can be ground-based data or true color very high resolution aerial images) and the spatial and radiometric resolution of the data, variations in species can be resolved from this transform or it can be used as a proxy for canopy and leaf architecture [16]. Ramachandra [18] maps forest fuel availability at the species level in India using a fusion of multi-spectral and panchromatic LISS data and an NDVI transform, achieving accuracies of 88 per cent at 5.8 m spatial resolution. More is said on pan-fusion and other 'up-scaling' techniques in Section 5.1. Baath et al. [17] use SPOT 2 and Landsat 5 images at 20 and 30 m resolution, respectively, and correlate

spectral reflectance with NFI data and their own field research. Volume, biomass and age are correlated with reflectance values. These correlations are extrapolated throughout the study area using the *k*NN method ($k = 1$). Poor pixel-wise agreement is discovered between the ground-data and the primary remotely sensed data, although accuracy levels improve considerably as pixels are aggregated at the stand-level. Shi et al. [19] calculate NDVI at a 1 km^2 using time series data of MODIS/Terra images to calculate net primary production (NPP) for different land cover classes. Those land classes that are most productive are assumed to have favourable energy qualities.

The value of a bioenergy resource assessment is partly determined by its ability to incorporate various source options. This is important because it extends the utility of the assessment in as much as it enables the analysis of a variety of conversion options down the road. It also enables the assessment of multi-biomass supply chains to the same facility which is usually more cost effective than single biomass supply chains [20]. This is especially the case when feedstock harvesting windows are narrow or when storage is logistically difficult. The methods discussed above only classify and calculate above ground woody biomass from forested areas. Biomass that comes from agricultural and municipal waste streams should also be calculated.

2.2. Agricultural fuels

Issues of species identification and biomass densities for agricultural biomass estimates are less complicated than for forest fuels for two reasons. First, growth patterns are controlled by human intervention. Second, agricultural land classification maps and/or tax parcel datasets help identify specific agricultural regimes [21]. Where such data is not available, secondary land classification maps and ancillary data (e.g., climatic data) are used to map out variables that are spatially correlated with suitable farm land, and a per-unit area yield and energy density based on predominant crop types can be applied [7,22,23]. Given that agricultural fuels are used primarily for food production, 'residue factors' are applied to each land parcel to distinguish biomass available for energy uses.

Voivontas et al. [24] use statistics of the spatial variability of agricultural residue yields to generate energy-relevant polygons of variable size with which to assess agricultural fuel potential on the island of Crete. Singh et al. [25] take a similar approach, but note that assuming bulk density figures by way of spatial aggregation is tenuous. Ramachandra and Shruthi [26] perform a 'talukwise' approach to aggregating statistical data and generate a chloropleth map of agricultural biomass availability within these various administrative units in a region in India. Given that agricultural fuels are aboveground biomass, remote sensing techniques can also be used. Indeed, Elmore et al. [27] use remote sensing data at 1 km^2 to assess rice straw potentials in China. Normalized Differential Vegetation Index values are used to calculate NPP, from which the mass of each energy source is derived.

Unless land-use data is available, dedicated energy crops cannot be distinguished from native woodlands via remote sensing. Thusly, for dedicated energy crops, a common method is to identify suitable land via existing soil, climatic, and land-use maps at appropriate scales, and to match this land with suitable bioenergy crops [7,28,29]. This ancillary data constitutes what Graham et al. [30] refer to as 'land availability variables', which the authors overlay and model on a 1 km^2 grid. Ramachandra [7] privileges 'multipurpose' species which can be used in other applications, careful not to assume that these crops will be used for energy simply as a function of their existence. 'Available land' restrictions will be discussed further in Section 3.1.

2.3. Waste fuels

Processed biomass that comes from waste repositories such as sawmills and municipal collection sites will provide a minimum and a maximum resource quantity depending on the time of year and on the nature of the manufacturing operation. This data is generally collected by way of industry data mining or mail surveys, and organized as point data in vector format [26,31–33]. The discrete nature of the biomass source makes vector data modeling highly relevant, which means that the sophisticated attribute data-handling capability of vector data models is employed. These attributes can include time-stamping, moisture content, and other relevant variables.

3. Exploitable bioenergy assessments

Collectively, the sum of the values discussed above represents the upper-bound of the total availability of forest, agricultural, and waste fuels in an area. In reality, however, theoretical bioenergy feedstock collection is restricted by spatial, ecological, economic, and harvesting restrictions. These are the variables that determine not only physical access, but economical access as represented by 'field gate' prices from which marginal cost curves can be generated when transportation costs are considered: these are discussed in Section 4.2. The resources available once these restrictions have been considered are referred to here as 'exploitable' energy. This is an important section because differences in the way that these variables are treated lead to very different conclusions about bioenergy availability.

3.1. Modeling non-energy uses and addressing the 'available land' question

Non-energy uses of biomass and environmental concerns over biomass removal from the landscape are among the most influential limiting variables for bioenergy projects. Shi et al. [19] develop an algorithm (Eq. (2)) which is applied to above ground biomass on a pixel-wise basis. This algorithm considers the ecological constraints of a given location and the economic competition for the potential feedstock:

$$P = B \times r \times m(1 - c - e - l) \tag{2}$$

where P represents exploitable energy; B is the biologically available biomass, represented in this case as net primary production (NPP); r is the fraction of biomass that is not primary yield (e.g., non-merchantable wood such as limbs and canopy crowns, or crop residues that do not enter the food-chain); m converts the biomass to an energy standard (e.g., higher heating value); c represents the fraction of r that should remain on site for soil maintenance and other ecological reasons (this represents an opportunity cost to farmers that needs to be redeemed); e represents economic competition from other biomass sectors such as the pulp and paper industry; and l represents losses throughout the collection system. Economically speaking, competition with the existing forestry and food industry is perhaps most important. Izguierdo et al. [34] model supply–cost curves using spatial data and note that biomass supply costs are the most difficult among the renewable energy resources to predict given its variable and fluctuating nature. Indeed, ancillary data such as soil conditions and topography are of crucial importance. The authors also note that land availability is a key limiting factor: as the most accessible and highest grade land and resources are used cost curves grow steeper.

In the context of concerns over land-use change and food security, defining 'suitable' or 'available' land for dedicated bioenergy land-uses is a precarious process. If this term simply means land

that is not currently being used for other purposes, then a macroeconomic model can be applied, bioenergy dedicated biomass is available for harvest in all economically favourable areas as in [29]. Bryan et al. [23] assume that all 'edible' landscapes will be replaced by 'energy' landscapes given favourable market conditions and price signals. Alternatively, a common approach is to perform overlay geoprocessing and to intersect the theoretical bioenergy map with land-use and/or land-cover maps containing land-use and land-cover data on susceptibility to degradation, agricultural activities, soil quality, location relative to water sources, and areas of concern or cultural significance. Spatial intersections of 'unsuitable' land cover types as defined by this ancillary data are then 'masked' from the energy availability map [17,21,22,35]. Other analysts simply choose to limit bioenergy production only to 'marginal' idle land – also a vaguely defined term – to ensure limited impact on other land uses [28].

3.2. Terrain and distance variables

The use of digital elevation models (DEMs) is important because topography physically limits mechanized forest and agricultural harvesting techniques and restricts the amount of biomass that can be sustainably removed from the landscape. Slope restrictions are dependent on the harvesting machinery available, the nature of the site conditions and the type of feedstock being harvested, and should be applied accordingly. Depending on these variables slope restrictions range from 20° [36] to 30° [5,12,21,37]. Panichelli and Gnansounou [38] increase harvesting costs in a step-wise fashion as the slope increases from 20° to 30°. For agricultural fuels DEMs are used to restrict collection rates on fields with slopes that exceed a threshold that makes a given plot of land susceptible to soil erosion. Residues are kept on the field in these cases to protect against winter winds and to retain nutrients during snow melt.

Spatial restrictions are also important. Current forest-fuel harvesting techniques typically extend to a maximum of 300–500 m from an existing road: this is known as the 'forwarding distance'. Beyond this distance a new logging road is required which adds to overall costs. To capture this spatial restriction, a common method is to overlay a digitized road network onto a theoretical energy density thematic map: see [17,39]. The road network is then buffered at a relevant forwarding distance. Clipping the original resource map to this buffer can represent the economically available energy in the area based on this spatial procurement restriction. Given that agricultural fuels and solid waste residues are already connected to existing transportation infrastructure, it is expected that this method captures all of the available feedstock from these two sources.

4. Net-yield bioenergy assessments

Those resources that are not subject to any of the restrictions discussed above are available for conversion into useful energy. The product of this conversion is 'net yield' energy availability. Indeed, net yields depend on the nature of the surrounding biomass, the rated capacity and the efficiency of the conversion technology, the size of the facility, and the procurement area. As such, net yield bioenergy availability is location specific. In the light of this the first crucial step in determining net-yield bioenergy availability is to consider potential candidate sites for bioenergy facilities. A review of the methodologies employed to locate facilities, and then to cost their supplies and to choose conversion technologies, is undertaken in this section.

4.1. Location analyses

Noon and Daly [31] developed one of the first geomatics-based bioenergy models and employed a user-defined location method; see also [21,40,41]. This method is unique in its ability to assess a predetermined interest in a specific location: e.g., an industrial site to be put back into operation, changing the feedstock of an already operational coal-fired electricity plant, or a rural town that is in need of public investment. This is especially important in cases where the goal is to streamline a biomass industry network, for example by locating a combined heat and power plant to serve the electric and process heat requirements of a sawmill. This method demonstrated the prohibitive nature of transportation costs for a bioenergy project, and a number of different location analysis methods have since been applied.

Supply-driven location analyses are used when there is some costing threshold that must be respected, and thus locating in areas with high energy densities is crucial. The location decision is driven by spatial concentrations of energy density. Voivontas et al. [24] choose the centroids of the spatial units with the highest energy densities to locate their facility. A cluster validity index might also be used on vector data: this method seeks a high ratio that represents an increase in the distance between two demand points, and a reduction in distance between supply and demand points [39]. Shi et al. [19] determine initial candidate sites based on road access to supply. These candidate sites are then aggregated using a 100 km threshold: the candidate site that is connected to the most other candidate sites within that threshold graduate to 'potential locations' which are subject to a more thorough analysis. Ranta [9] states that supply-driven analyses are best for technologies not limited by proximity to a demand – e.g., pyrolysis oil or pellets which are dense forms of biomass that can travel greater distances without relinquishing positive net energy yields.

Demand-driven locations, the third category of location methods, are most relevant to investor decisions since they begin with a market assessment [42,43]. They are based on factors such as population densities and the lack of heating or electricity capacity in an area. In this case, a desired output capacity of a specific energy vector (e.g., heat, power, liquid fuel) is determined, and the location algorithm privileges those factors which enable this demand-satisfaction including location relative to specific feedstock and to relevant distribution terminals. For examples of variations of this method see [42–44]. Similar to this approach is to privilege cities that have existing infrastructure that can support a bioenergy facility. In [6], the population of a city is used as a surrogate for water availability, labour availability, travel infrastructure, and other criteria relevant to siting decisions. This type of analysis is especially important in cases where international markets are being considered, as is the case for biomass pellets: in this case, access to rail lines and deep water ports might be a crucial concern for siting decisions.

A fourth common location method, which can take the form of a supply or a demand analysis depending on which criteria are privileged, is multi-criteria analyses (MCA) via overlay geoprocessing [36,45–48]. In this method the variables relevant to the siting decision – e.g., distance to supply sources, distance to existing infrastructure, land-cover and land-use characteristics – are represented as individual maps wherein each specific location has a rank value for a given variable. Each variable is assigned a relative weight, which may be determined by inputs from 'experts', stakeholders, decision-makers, and community members. Each pixel or feature value for a given variable intersects with other variables at the same location assuming all maps are co-registered, and optimal sites are represented by the largest overall value. This approach acts as a useful 'filter' to determine which locations are more suitable [46], and since it can be flexible as opposed to technology-specific

it is useful in a comparative approach. This method can use either vector or raster data models, but it is important to note that each data model has limitations and even when using the same dataset can lead to different conclusions [49].

All of the methods discussed above optimize for transportation costing *after* candidate sites have been identified, and thus plant locations are independent variables in transportation costing procedures. If subsequent transportation cost assessments – which will be discussed later – return poor values for even these candidate sights, it can be concluded that the entire area under study is incapable of supporting a bioenergy project under existing conditions. Alternatively, transportation and routing decisions can be determined endogenously to location decisions. In these cases, locations are chosen based upon optimizing an objective function such as minimizing transportation cost or maximizing energy generation in the context of specific rule-sets, including avoiding supply-area overlaps [9,50] or traffic congestion [51].

Location-allocation modeling privileges the marginal cost of biomass delivery [52]. Facilities can be located sequentially and thus the spatial effects of competition for resources can be modeled. When the conversion process is chosen *a priori*, specific logistical issues can be factored into this type of analysis. Location-allocation modeling is perhaps the most complex geo-processing task and is difficult to calculate over long distances. Indeed, Ranta [9] only optimizes at a 10 km radius in a step-wise fashion whereby the most optimal sites 'graduate' to the next step. Its greatest benefit is that it optimizes for the cost of delivered feedstock which is a decisive factor in bioenergy viability.

4.2. Transportation costing

Each energy conversion facility has what might be called a 'fuel shed', which defines the boundaries of its procurement area [48]. This is the radius at which economically feasible resources can be collected. Of course not all fuel sheds are the same given that they depend on the scale of the conversion facility, the type of technology being employed, the complexity of the road network, and the bulk density of surrounding biomass. Indeed, fuel-sheds, delivered feedstock costs, density of feedstock availability, the scale of the facility, and the conversion choice are co-dependent. To simplify these matters some analysts choose the conversion technology *a priori* [10] while others simply apply a common procurement radius to all options [9].

Network analysis and path finding techniques via vector geo-processing are useful methods to assess transportation costs, since they are adept at measuring and optimizing for distance and connectivity. They enable a user to dynamically model realistic network conditions including turn restrictions, speed limits, connectivity, and traffic conditions, as well as allowing the user to introduce context-specific parameters [53]. All exploitable energy resources need to be reformatted into vector data and connected to a digitized road network. In the case of raster data, the pixelated monetary and energy values as discussed above can be aggregated in 'collection nodes' on the road network using zonal statistics. These nodes are often represented by road intersections [54]. Shi et al. [19] divide very long roads into several lines to generate more nodes, thereby reducing the level of aggregation and increasing accuracy. Transportation routes to the facility location can then be assessed based on a network analysis which can minimize some objective function – e.g., distance or cost – via linear programming [43]. Alternatively, a pixel-based approach can be taken in which the cost of transporting material from one pixel to any other pixel is calculated [30]. In either case, assumptions to be made include loading/unloading costs, maximum capacity per truck, average transportation speeds, the cost of transportation fuel and the tortuousity of the road network. The latter depends on the nature of the road network – tortuousity factors are higher for logging roads and lower for city roads and highway networks. One must also consider loading regulations exercised within a given jurisdiction.

4.3. Assessing the conversion option

Bioenergy technology choices are made complex by the fact that it is the only available renewable energy source that can satisfy base-load electricity, heat, and motive end uses. These conversion options generally require feedstock with specific biochemical and physical properties. The conversion technology dictates the extent to which a feedstock is immediately useable (e.g., biogas facilities), useable after physical treatment (e.g., pellets and co-combustion), or useable after chemical treatment (e.g., isolating cellulose for ethanol production) [36].

Based on the conversion pathway, facility size and efficiency, and using the spatially explicit resource assessment developed using a combination of the methods discussed above, net energy returns can be quantified at a given location using systems analysis to model and estimate energy balances. To effectively assess net yield energy availability, however, it would be prudent to assess a variety of different conversion options rather than choosing the options *a priori* or restricting the analysis to specific source options and conversion pathways. Elaboration on these issues is provided in Section 5.3.

5. Making connections and addressing gaps in the literature

The review above demonstrates a number of variations in data selection, data models, spatial and thematic resolution, and other key methodological parameters that are interdependent with the purpose and the outcome of the model. The purpose of this section is to weigh in on and address some of the issues raised in making these selections.

5.1. Data acquisition, modeling, and resolution

A high level of thematic detail is achieved when using ground-based measurements and referencing it via vector modeling. Given the discrete nature of vector data models, however, they are unable to reflect the continuity that typifies aboveground vegetation [13]. Most importantly, when data is stored or reconfigured into polygon format, spatial homogeneity over the entire parcel is assumed. This limitation is significant given that bulk density is a crucial variable for the cost and yield of silvicultural and harvesting operations, and thus for overall bioenergy viability. In cases where distribution is more important than averages, polygon-based formats which generally characterize NFI data are flawed. Furthermore, vector data models rely on ground-based data collection or manual photo-interpretation, both of which can be labour intensive and thus costly if a large area is to be assessed. Indeed, for analytical purposes there are two types of bioenergy sources: above ground vegetation and processed biomass. The former is continuous over the landscape, while the latter is discrete and has specific source points. The former is thus best captured with remote sensing techniques and represented in raster data models, and the latter with vector data models captured using industry data and mail surveys that are later mapped out in a GIS. In either case distance and bulk density are important considerations, and so when geo-rectifying a dataset it is prudent to choose a projection system that preserves distance and area.

Image resolution of remotely sensed data is a limiting factor for renewable energy assessments [37]. Das andRavindaranth [15]

state that a resolution of at least 100 m is required, which would classify the data as medium resolution. This enables relatively accurate forest structure estimations over the regional or landscape scale. Coarser data, such as that used in [19,53], is suitable only for global or national level estimations. Especially if the purpose is to extend the analysis into a techno-economic assessment or to inform a local audience, this may not suffice given the small scales at which bioenergy supply chains generally operate. In addition to this, biomass is far more heterogeneous at local or regional scales than a national level analysis might otherwise imply. Indeed, low spatial resolution means that averages must be privileged at the expense of distributions.

Thematic accuracy from remotely sensed data analysis is highly dependent on spatial resolution. Biomass estimations for non-energy applications (e.g., fire management, wildlife habitat management) experience considerable difficulties generating consistent correlations between ground-based forest biophysical variables and medium/course spatial resolution spectral data. To enhance spatial resolution, Ramachandra [18] uses a pan-fusion technique whereby the 23.5 m resolution multi-spectral data is 'up-scaled' to the 5.8 m panchromatic resolution by way of a pan-sharpening algorithm. The author notes favourable accuracy levels at the stand level as a result. It should be noted, however, that methods which merge datasets of different resolutions into a single image affect the spectral and radiometric properties of the data [55], and should be applied carefully. Less invasive techniques to increase spatial resolution include multi-resolution analysis, such as correlating the spectral responses of very high resolution airborne imagery with high or medium resolution satellite imagery [56], or using the discriminatory power of the spatial domain rather than the spectral domain using very high resolution data [57]. This includes the addition of texture metrics into the classification procedures using very high resolution ortho-imagery [58,59], or the incorporation of contextual and structural relationships [60,61]. These methods have yet to be adopted in the field of bioenergy assessments. It is important to note, however, that the classification methods developed by image scientists may not be directly transferable, as in many cases quantitative procedures need to be adapted to site-specific and sensor-specific characteristics [16,62]. More basic research is required to derive energy-relevant information from remotely sensed data, and as such it is important to make use of ancillary data and NFI data rather than relying solely on remotely sensed data.

Having been critical of the data used in previous studies, it is important to recognize that broad area bioenergy analyses are limited by data availability. Gómez et al. [5], for instance, were able to disaggregate their data into the relative dominance of 18 families as a consequence of having up-to-date and high level NFI data, while Viana et al. [10] are forced to work with NFI data that is highly aggregated spatially and thematically. Similarly, authors using remotely sensed data are limited by the cost of high resolution imagery. Two other factors control the data and the techniques employed. First is on the emphasis of the assessment which can range from visualization and the identification of 'hot spots' where further research and resources should be targeted [37,48] to detailed quantification of supply cost curves [30,34]. Second is the audience to which the assessment is oriented. This is especially influential in terms of the scale of the analysis and of the spatial and thematic resolution that can be achieved. Very high resolution multispectral imagery or LiDAR data, for instance, can be used at small scales – e.g., at the fuel-shed scale – if the audience is an interested investor and if a location is pre-defined. To attain information at a scale relevant to policy-makers, however, coarser resolution data is in most cases necessary. For the sake of flexibility, Ayoub et al. [39] develop a two level decision support system that can be made to apply at national and regional levels of organization and management.

5.2. Assessing the sustainability of bioenergy projects

Sustainability is a function of spatial and of temporal variables. Many of the spatial variables are discussed above in Section 3.1. Ultimately, investigators should look to land-use and environmental regulations in their own jurisdiction for guidance on which variables to include in the analysis. An issue that does not receive enough attention in the literature, however, is the temporal aspect of sustainability.

Bioenergy projects must be viable over the lifetime of their operation. Three temporal aspects are important to consider: (1) resource patterns change, (2) energy demands are modified, and (3) incumbent energy prices and the cost of emerging technologies fluctuate. The latter two categories will effectively push the boundaries and blur the lines between theoretical, exploitable, and net yield energy availability. This is because as demand increases and resources are put under more strain those supplies that were once un-exploitable for economic reasons will slowly become competitive. Furthermore, as technology improves it is likely that bioenergy conversion facilities will be able to accept a broader range of feedstock types and/or will become more efficient, while at the same time harvesting techniques will improve, perhaps reducing the size of fuel-sheds. The main concern, then, is how bioenergy *resources* will change because a steady supply of resources is the most important parameter in the technology utilization rate, and thus the viability of an energy project through time.

An important strategy identified in the literature is that biomass growth models are made energy-relevant [11,17,38]. This includes incorporating the effects of different harvesting techniques on future yield patterns within a fixed area – i.e., the fuelshed [17]. Trend analyses based on net primary production can also be used [19,27]. Papadopoulos and Katsigiannis [63] use historical statistical data of productivity and expected energy values for feedstock to estimate the inter-annual variations in supply that a bioenergy facility might expect. The effects of land conversion are also important [64,65], which suggests a macro-economic component to feasibility analyses. Issues of space-time representation remain a focal point of research in geomatics, and the issues are especially relevant to bioenergy modeling.

Overall net-energy returns of a bioenergy operation are a matter of considerable debate. In the light of this, analysts must be careful of privileging supply cost curves at the expense of net energy returns. A bioenergy system may reduce its costs by purchasing feedstock from a more distant jurisdiction that can supply said feedstock at a reduced price because of favourable growth patterns or subsidies, even though the energy required to transport the feedstock may not be returned by the bioenergy production process. Geomatics can be used to delineate fuel-sheds based on the distance that a given feedstock can travel without using more energy than it can provide through contemporary conversion methods. Subsequently, lessons might be learned from fossil energy extraction patterns which maintain an optimal reserve/production ratio. Such a ratio applied to biomass resources within the fuel-shed can ensure that the rated capacity of the plant requires a quantity of feedstock that is below the annual growth rate or average productivity within the procurement area to ensure that the facility can withstand unforeseen feedstock disturbances such as fire or drought. This ratio would, of course, depend on growth rates and thus incorporate mean annual increments or NPP. Linking this directly to the rated capacity of the plant would help to ensure the sustainability of the bioenergy facility over its lifetime, while at the same time ensuring that loading capacities, and thus process economics, are optimized.

5.3. Choosing among the options: site specific analyses

Shi et al. [19] state that "the potential of spatial information technologies in the biomass energy sector has received considerable attention, but there is a general deficit of exemplar case studies illustrating the comprehensive process beginning from a biomass survey using remote sensing and ending at a site selection using GIS." This review illustrates substantial progress in this regard. Indeed, a number of siting methods have been employed. If the biomass conversion technology is chosen *a priori* – for example, ethanol production – then the location can be optimized based on the relative location of specific feedstock types, and particular forms of transportation procedures can be assessed. If the conversion technology remains open ended, then the siting decision can be less specific and consider a complex of variables. Gómez et al. [5] argue that, especially over a large study area, it is impractical and pointless to optimize for every possible plant location. This is true to the extent that supply chains are highly complex and thus difficult to capture in a mathematical model, and that not all energy related decisions are made by a centralized authority or on the basis of the variables captured by the model, and thus the perfectly rational allure of this level of optimization is disconnected from the reality of decision-making. Regardless of the method used, the key to a relevant assessment is to locate the facility so that the site-specific nature of bioenergy viability can be modeled.

There is a considerable range of existing and emerging bioenergy technologies that determine 'technical capacity' and thus net yield energy availability. It is clear from this review, however, that few geomatics-based studies assess even a sample of this range. Most investigators have chosen instead to limit the options that are assessed based on analyzing only a single source option or a single conversion pathway/energy vector. Bioenergy is not a 'one size fits all' source or conversion option, and should not be treated as such. Indeed, more work needs to be done comparing bioenergy options in the context of local patterns of supply and demand. To the extent that form, time, and place are crucial aspects of energy decisions [66], they need to be considered collectively, and thus all available options need to be evaluated and compared on a site-specific basis.

A number of studies have compared the techno-economic performance of various bioenergy conversion technologies independently of geography using systems approaches and hypothetical or assumed feedstock [67–71]. The geographic nuances that are decisive to technology performance are not considered. Future comparisons of bioenergy technologies need to bridge the gap between geomatics-based bioenergy resource assessments and location analyses, and comparative bottom-up techno-economic systems analyses. For comparative purposes, the boundaries of the system need to be consistent across the options. A technology database that defines the parameters of each conversion system should be soft-linked with the resource database of a GIS, or a 'clearinghouse' approach can be employed, to pull in the respective biomass availability and feedstock delivery variables. In this way, energy-density thematic maps not only serve as a way to communicate the distribution of bioenergy feedstock, but also serve as a crucial module in a technological assessment. This will address concerns raised that there is too much research on supply, and not enough on issues of place, time, and form [66]. Additionally, it will bring certainty to the biggest risk for a bioenergy facility: long term feedstock procurement.

6. Conclusion

A lack of baseline information at the agenda-setting stage of public and private energy planning prevents decision-makers from taking bioenergy seriously. Indeed, robust information is the lubricant for decision-making and is the only way we can minimize the unintended consequences of those decisions. This baseline information needs to be site-specific to take seriously the spatio-temporal nuances that are consequential to bioenergy feasibility. To this end, geomatics techniques are crucial. Hopefully this review provided future analysts with a solid footing upon which to develop these techniques further.

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